CONTRIBUTED PAPER

Methodology for Maximizing Information Transmission of Haptic Devices: A Survey

This article surveys the information transmission capability of haptic devices, and ways of maximizing it.

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ABSTRACT | This is a survey article on the information transmission capability of haptic devices and ways of maximizing it. It is intended for readers who are engineering professionals interested in developing novel haptic interfaces for a variety of applications but are not necessarily trained in haptic science or human user research. We posit that the ultimate goal of any interface is the exchange of information between a machine and a user, and as such, the evaluation should involve estimating the information-transmission capability with human users. We conducted a literature survey on studies of haptic devices evaluated with human users using an information theoretic framework. Our goal was to discover and summarize best practices that can lead to high information transmission. The results confirmed findings from our own previous studies, uncovered new ways to effectively increase information transmission, and pointed to the need for broader dissemination of proper experimental methodology. We, therefore, present a concise yet comprehensive tutorial on psychophysical methodology for estimating information transfer (IT) and IT rate with humans, survey results on the typical IT achievable with haptic devices, and guidelines for maximizing information transmission with any human–machine interfaces. Although we focus on haptic systems, the information-theoretic framework, the psychophysical methods, and the guidelines presented in this article are applicable to other sensory modalities and multimodal interface systems also.

KEYWORDS | Haptics; human–machine interface; information theory; information transfer (IT); information transmission; interface; psychophysics.

I. INTRODUCTION

The word haptics refers to sensing and manipulation through the sense of touch. It consists of tactile and kinesthetic sensing. The term cutaneous or tactile sense refers to the awareness of stimulation on the outer surface of the body mediated by different types of mechanoreceptors in the skin [1]. For example, vibration on the skin is a form of tactile stimulation. The term kinesthesis or proprioception denotes the awareness of joint-angle positions and muscle tensions mediated by sensory receptors embedded in the muscles and joints [2]. A force-feedback device that exerts forces on the user provides kinesthetic stimulation. Haptic systems can include cutaneous and/or kinesthetic devices as well as thermal displays. Modern haptics is concerned with the science, technology, and applications associated with information acquisition and object manipulation through touch, including all aspects of manual exploration and manipulation by humans, machines, and the interactions between the two, performed in real, virtual, teleoperated, or networked environments [3].

With the ongoing and increasing interest in haptic (touch-based) interfaces for virtual and augmented reality, human–robot interaction, gaming, and just about any human–machine system, the question arises as to how much information can be transmitted effectively through

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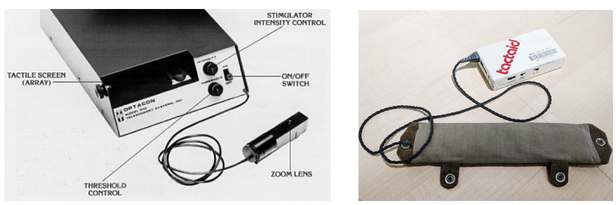
Fig. 1. ***Tadoma method of haptic communication of speech used by individuals who are both deaf and blind. Shown are Nat Durlach (center, with normal sight and hearing) and two deaf-and-blind individuals who are having a three-way communication (photograph courtesy of Hansi Durlach).***

the sense of touch. Estimates vary widely, with the highest reported upperbound being 56 b/s using simple binary signals at the fingertip [4]. A more conservative and perhaps more realistic estimate of haptic communication capacity is 12 b/s for a natural speech communication method used by individuals who are both deaf and blind [5]. In this method called "Tadoma," the "listener" places his/her hand on the talker's face and, in the absence of any visual or auditory cues, monitors the articulatory process associated with speech production (see Fig. 1). Research has shown that the most important haptic cues employed by the Tadoma users include lip movement, jaw movement, oral airflow, and laryngeal vibration [6]. The 12-b/s information-transmission rate can be viewed as an existence proof and benchmark that human performance with any haptic devices can be compared to.

A similar upper bound was reported for the OPtical to TActile CONverter (Optacon) [7], a reading aid for the blind that converted images of printed materials to vibrational patterns on the index finger. The portable system consisted of a small hand-held camera and a 24×6 pin array that measured 2.7×1.1 cm, roughly the size of the index fingertip [see Fig. 2(a)]. Whenever a photocell detected a black pixel, the corresponding pin vibrated. Studies with the Optacon showed a reading rate of 40 words per minute (wpm) by the best participant in one study [8] and 70–100 wpm by two sighted "extraordinary observers" in another study [9]. These reading rates correspond to 5.3 and 9.3–13.3 b/s, respectively, assuming an information content of 8 bits per word (see note 13 in [10, p. 1008] for assumptions). The ability for a haptic device to transmit 12 b/s through the sense of touch was also demonstrated in the laboratory with the Tactuator, a multifinger display interfaced with the thumb, index finger, and middle finger, using abstract haptic symbols [10] (see Fig. 6 and further details in Section III-A). In comparison, typical performance with other systems designed to communicate speech or text has shown much lower information rates. For example, the Vibratese coding consisted of 45 symbols that varied in five vibrator locations, and three intensities and three durations per vibrator. It supported all letters, all numerals, and several frequently encountered short words such as "of," "the," and "in" [11]. The information rate for the Vibratese language was 5.1 b/s (38 wpm) [12]. Results for Morse code transmitted via electrocutaneous stimulation and up-down finger motions were much lower, 1.3 b/s (10 wpm) [13] and 2.7 b/s [14], respectively, presumably due to the inefficiency of the code itself. Among the tactile aids for the hearing impaired, Tactaid II or Tactaid VII was the most widely distributed devices. They consisted of a small processing unit with an embedded microphone that could be clipped to a belt or fit into a shirt pocket, and a harness with two or seven resonant-type vibrators [see Fig. 2(b)]. The acoustic signal of speech was processed through an array of bandpass filters with increasing center frequencies. The output of these filters was rectified and used to modulate the amplitude of the corresponding vibrators [15]. When used alone, the Tactaid devices could convey useful information regarding environmental sounds [16] but could not be used for understanding speech without lip reading [17].

We revisit the question of whether it is possible to achieve 12 b/s or higher with engineering systems that interface with the human skin. This prompted us to conduct a survey of recent studies on the information transmission capabilities of haptic devices and look for evidence that sheds light on how one should go about achieving high information transmission rates.

The findings from this survey are important to the Proceedings readers for several reasons. First, there is a growing interest in the use of haptics technology in consumer products. Objective performance evaluation with human users is important. Information theory provides a framework for a direct comparison of different technologies in terms of bits of information transmitted or information transmission rate in bits per second. It is our goal to promote information theory among designers, engineers, and psychologists who are involved in innovating new haptic systems for human–machine interaction and communication. Second, an information theoretic framework is even more attractive for consideration of multimodal interfaces.



(a) (b)

Fig. 2. ***(a) Optacon (photograph courtesy of Telesensory Corporation). (b) Tactaid VII (photograph courtesy of Pascal Getreuer).***

The information-transmission capabilities through different sensory channels (vision, audition, touch, etc.) can be quantified, compared, and combined (when different sensory channels encode information independently). Third, information theory also provides a tool for the quantitative study of redundant versus nonredundant coding of information through different sensory channels. Fourth, such a framework is generally applicable to any other communication system, whether machine-mediated or not. For example, information transfer (IT) rates have been estimated for speech communication through audition, vision, and touch modalities [18]. Therefore, we aim to introduce information theory to any Proceedings readers who are developing haptic or multimodal human–machine interfaces and who wish to evaluate the system performance quantitatively with human users. However, it is not the intention of this article to provide an overview of haptics technologies and applications per second.

This work began as part of an initiative at Facebook's Building 8, now known as Facebook Reality Labs, to develop haptic communication systems [19]. It is the result of a close collaboration between researchers in academia and industry who have informed, inspired and challenged each other. It is an ambitious undertaking to enable communication through the skin for people with all levels of sensory capabilities. By using an information theoretical framework to compare existing haptics systems, we can visualize and understand the trends of what is achievable, where the fundamental limitations are, and where opportunities lie to push the limits.

This article is organized as follows. We present in Section II, a tutorial on information theory as applied to human performance studies and the corresponding psychophysical methodology. The tutorial is self-contained to provide the background information needed to understand the rest of this article. It is the most detailed treatment of IT and information rate in terms of experimental design, data analysis, and interpretation of results in one place. The methods and findings of the survey study are presented in Section III. This is the first time where results from 35 published haptic studies are analyzed and compared. Section IV concludes with general guidelines for building high information throughput systems, backed up by existing research data.

II. PSYCHOPHYSICAL STUDIES OF HAPTICS USING AN INFORMATION THEORETICAL APPROACH: A TUTORIAL

Psychophysics focuses on the quantitative relationship between physical stimuli and the perception of the stimuli. The development of techniques that enable the measurement of sensory processes and of statistical models characterizing the performance of the human operator has been an essential part of psychophysical research. Over the past two decades, psychophysical techniques have become an integral part of hardware and software development and evaluation in haptics research. A recent review provides an overview of the Fechnerian psychophysical methods (the method of constant stimuli, the method of limits, and the method of adjustment) and post-Fechnerian techniques (signal detection theory, adaptive techniques, information transfer, scaling techniques, and multidimensional scaling) that are applicable to haptics research [20]. Approaches based on Bayesian and maximum-likelihood integrators are also gaining popularity [21], [22]. Although most psychophysical techniques quantify our sensory capabilities and limitations due primarily to peripheral mechanisms and are subject to various effects that arise in the cerebral cortex, the information theoretical framework focuses more on our ability to process information due to more central effects such as memory. As psychological concepts, uncertainty, information in stimulus and response, and IT characterize a human as a noisy communication channel [23]. As such, human performance can be specified in terms of IT (in bits) or IT rate (in bits per second). Information theory provides a unified approach to assessing the information-transmission capability of any devices through human users and allows a direct comparison of visual, auditory, and haptic systems in the same units of bits and bits per second.

We use the example of auditory pitch perception of piano keys to illustrate the difference between the two tasks of discrimination (limited primarily by one's peripheral sensory resolution) and identification (limited by one's ability to memorize the sight/sound/feel of an object or event; i.e., the central nervous system). In a discrimination task, two piano keys are played one after the other, and an observer is asked to pick out the key with the higher or lower pitch. Anyone with normal hearing can discriminate the pitch of two adjacent keys on a keyboard, whether or not the person is musically trained. In an identification task, one of the keys is struck in isolation and the observer is asked to identify which key it is. This is a much harder task as it requires the observer to have a perfect memory of all the 88 keys on a keyboard, the so-called perfect pitch or absolute pitch. Except for a minority of individuals who are born with absolute pitch, even musically trained individuals cannot identify the pitch of any piano key without a reference (e.g., middle C). This article is concerned with the latter; that is, identification tasks where an observer needs to identify the location of a tap on the skin or the language symbol a haptic pattern encodes.

What makes information theory especially attractive for studying and comparing any human–machine interface system is the concept of channel capacity. Simply put, it states that as the complexity of stimuli increases, the maximum amount of IT will increase initially and then reach a plateau (see Fig. 3). This maximum IT is called the channel capacity. This is an important metric as any communication system should strive to reach the human channel capacity for maximum effectiveness. Designing a system that delivers less or more than the channel capacity

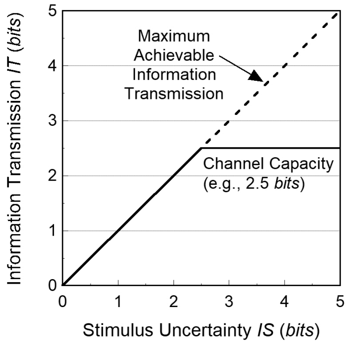


Fig. 3. ***Illustration of the concept of channel capacity. See (4) for the mathematical definitions of IS and IT.***

would be wasting either the human or the machine's capabilities, respectively. Consider, for example, the question of how many tactors should be worn around a belt to provide orientation information to its wearer. Imagine that eight tactors are placed in equal distance from each other, or 45° apart, on the belt. The wearer is asked to identify the location of any tactor when it is turned on. If the stimulus set contains only the four tactors at the front, back, left, and right sides of the belt, then most wearers can perform the task perfectly. If all eight tactors are included in the stimulus set, however, then the wearer will start to make errors [24]. A majority of localization studies report performance in terms of the percent-correct scores which are highly dependent on the number of stimulus alternatives (e.g., number of tactors placed around the belt). However, in "mission critical" applications where a tactile belt is used to display waypoint information [25] or a 2-D tactile array is used for navigation guidance [26], [27], we argue that identification or recognition accuracy needs to be near perfect for such systems to be of practical value. The beauty of information theory as it applies to human perception study is that from the stimulus-response confusion pattern of the eight tactors, the experimenter can estimate channel capacity, and hence the maximum number of tactors that can be correctly localized on the belt. There is no need to keep repeating the experiment with 1, 2, ..., and 8 tactors until one reaches the maximum number of tactors that can be correctly localized.

In what follows, we present a tutorial of information theory as it applies to psychological research based on the seminal work by Garner [23], [29], Garner and Morton [28], and Miller [30], [31] that have strongly influenced the research in this field including our own previous work (see [18] and [32]–[35]). For example, Garner [23] laid out the concepts and formula presented in Section II-A. Miller [31] coined the term "magic number 7 ± 2" for channel capacity, and his work is summarized in Section II-B. Our own previous experimental data supported the concept of channel capacity as illustrated in Fig. 3 [34]. In these studies, the human observer is the communication channel itself. The input of the communication system consists of a discrete set of stimulus alternatives, and the outputs are responses to a random sequence of the stimuli. This is different from the signal compression research where speech, audio, image, and/or video are coded, distorted, and transmitted, and the human observer judges the signal quality after the signal has been transmitted (see [36] for a review, and [37] and [38] for an example on haptic data compression). It should also be noted that we consider the case where the goal is to design a haptic display (device and the associated stimulus set) that minimizes response errors in an absolute identification task (defined in Section II-A) given the capacity-limited human communication channel. This is not necessarily "optimal" as rate-distortion theory would suggest "that the goal for perception should not be perfect identification, but rather the minimization of error according to some cost function" (see [39, p. 185]). Furthermore, as eloquently explained in [39], when a participant makes an identification error, the response tends to be close to the correct one rather than being random. This behavior can be modeled within the rate-distortion theory framework with a cost function that minimizes absolute error (Model L_2 [39]). However, a different model (L_3) is needed in order to explain the "bow effect" that describes the phenomenon that identification performance is better at the boundaries of a stimulus range. It should also be noted that channel capacity and the bow effect (also termed "perceptual anchors") have been successfully modeled by extending signal detection theory to more than two stimulus alternatives (see, for example, a series of publications by Durlach and Braida on auditory intensity perception, starting with [40] and [41]). Therefore, what is presented in this section is only a starting point—much work remains in both theoretical modeling and experimental methodology. It is our intention to attract attention to this important research direction. Interested readers should also consult Shanon's original work on information theory for nonhuman communication systems (see [42] and [43]).

A. Absolute Identification Experiment and Estimation of Information Transfer

A typical way to measure IT is to run an absolute identification experiment. First, a set of K stimuli (S_i, $i = 1, \ldots, K$) is constructed. A corresponding set of K responses (R_j, $j = 1, \ldots, K$) is then assigned so that R_j is the correct response to S_i when $j = i$. On each trial, the participant is presented with a stimulus randomly selected from the stimulus set. The participant chooses a response from the response set after each stimulus presentation. The experimental results are tabulated in the form of a stimulus-response confusion matrix with rows corresponding to stimuli and columns responses. The entries in the main diagonal of the stimulus-response confusion matrix represent the number of "correct" trials. Error trials distribute among the nondiagonal cells in the confusion matrix.

IT is then calculated from the confusion matrix. The quantity IT measures the increase in information (or reduction in uncertainty) about the signal transmitted from knowledge of the signal received. Theoretically, we can express IT in terms of probabilities. For a particular stimulus–response pair (S_i, R_j), the quantity IT is given by

$$\mathrm{IT}(S_i, R_j) = \log_2 \frac{P(S_i \mid R_j)}{P(S_i)} \tag{1}$$

where $P(S_i|R_j)$ is the conditional probability of S_i given R_j, and $P(S_i)$ is the *a priori* probability of S_i. The average IT is given by the weighted sum of individual IT values

$$\begin{aligned} \mathrm{IT} &= \sum_{j=1}^{K}\sum_{i=1}^{K} P(S_i, R_j) \log_2 \frac{P(S_i \mid R_j)}{P(S_i)} \\ &= \sum_{j=1}^{K}\sum_{i=1}^{K} P(S_i, R_j) \log_2 \frac{P(S_i, R_j)}{P(S_i) \cdot P(R_j)} \end{aligned} \tag{2}$$

where $P(S_i, R_j)$ is the joint probability of stimulus S_i and response R_j, and $P(R_j)$ is the probability of R_j.

Given a stimulus–response confusion matrix, the probabilities in the IT equations can be approximated by the frequency of occurrence to obtain the maximum likelihood estimate $\mathrm{IT}_{\mathrm{est}}$

$$\mathrm{IT}_{\mathrm{est}} = \sum_{j=1}^{K}\sum_{i=1}^{K} \frac{n_{ij}}{n} \log_2 \left(\frac{n_{ij} \cdot n}{n_i \cdot n_j}\right) \tag{3}$$

where n_{ij} is the number of times the joint event (S_i, R_j) occurs, $n_i = \sum_{j=1}^{K} n_{ij}$ and $n_j = \sum_{i=1}^{K} n_{ij}$ are the row and column sums, respectively, and $n = \sum_{j=1}^{K}\sum_{i=1}^{K} n_{ij} = \sum_{j=1}^{K} n_j = \sum_{i=1}^{K} n_i$ is the total number of trials collected.

Assuming that performance is not perfect (i.e., the stimulus response confusion matrix contains errors in the off-diagonal cells), $\mathrm{IT}_{\mathrm{est}}$ represents an estimate of the channel capacity for the specific stimuli set tested. A related measure 2^{ITest} is interpreted as the number of stimuli that can be correctly identified without error, assuming that $P(S_i)$ is the same for all stimuli.

Two related measures, information in stimulus (IS, also known as the input entropy or stimulus uncertainty) and information in response (IR, or output entropy), can be expressed theoretically in terms of probabilities

$$\begin{aligned} \mathrm{IS} &= -\sum_{i=1}^{K} P(S_i) \log_2 P(S_i) \\ \mathrm{IR} &= -\sum_{j=1}^{K} P(R_j) \log_2 P(R_j) \end{aligned} \tag{4}$$

or in terms of the frequencies of occurrences, n_i/n for $P(S_i)$ and n_j/n for $P(R_j)$, that can be obtained from the stimulus–response confusion matrix. The stimulus uncertainty IS is simply $\log_2 K$ when all K stimulus alternatives are equally likely (which is typically the case). Therefore, IS is directly related to the size of the stimulus set. The quantity IR provides a measure of the participant's response bias. The value of IR is maximum if the participant uses all response labels equally likely. It cannot exceed $\log_2 K$.

The value of IT may never exceed IS in any absolute identification experiment. As shown in Fig. 3, for small values of K or IS where the participant is able to identify all stimuli perfectly, IT = IS = IR. As IS increases, IT plateaus at a maximum value which is the channel capacity.

B. Miller's Magic Number 7 ± 2 and Dimensionality

Before we proceed into the practical issues concerning absolute identification experiments, it is worth a discussion on the typical values of channel capacity and the definition of perceptual dimension. Miller summarized the channel capacity of most perceptual dimensions to be 7 ± 2 levels (the so-called "magic number 7 ± 2"), or equivalently, 2.3–3.3 bits [31]. The examples used in Miller's article were concerned mostly with visual and auditory stimuli. The channel capacity for haptic stimuli appears to be 2.0 bits or less; for example, 1.0–2.0 bits for finger span, joint angle, force magnitude, and stiffness identification [44]–[46]. One reason for the discrepancy may be the lack of a clear definition for perceptual dimensionality. The number "7 ± 2" is the channel capacity for a stimulus set varying along one perceptual dimension, yet a precise definition of dimensionality does not exist anywhere in the literature. The closest Miller came to giving a definition was "the number of independently variable attributes of the stimuli" [31, p. 87].

Intuitively, it may seem obvious that the number of perceptual dimensions should be equal to the number of physical parameters needed to generate the stimulus alternatives. For example, the amplitude and frequency of an auditory tone (two physical parameters) determine its perceived intensity and pitch (two perceptual dimensions), respectively. In the haptic modality, weight refers to the physical dimension related to perceived heaviness. Upon closer examination, however, physical and perceptual dimensions need not be the same and either can be larger than the other. For example, one of the examples cited by Miller [31] was a channel capacity of 3.3 bits for the visual identification of line direction, or angle of inclination from Pollack. Although the only physical parameter being manipulated was the angle of the lines, one may argue that the perception of lines at different inclinations operated in a 2-D perceptual space, which could account for the relatively high channel capacity. Another example of one physical parameter leading to multiple perceptual dimensions can be found in the haptic perception of single- or multi-frequency sinusoidal stimuli.

At least three distinct sensations are associated with single-frequency sinusoidal stimuli as the stimulation frequency increases from 0 to 400 Hz: slow motion, flutter [47], [48], and smooth vibration. Furthermore, when two or three sinusoidal signals are combined in a stimulus (e.g., a 4-Hz motional signal combined with a 300-Hz vibration, or the combination of a 2-Hz motional signal, a 10-Hz flutter, and a 150-Hz vibration), the sensations associated with the sinusoidal components remain intact in the sense that one clearly perceives the presence of a movement, a flutter, and a vibration in the multifrequency stimulus signal [10], [49], [50]. In other words, one physical variable of frequency is mapped to a 3-D perceptual space. There is also evidence that two physical variables can map to one perceptual dimension. In a study of simulated virtual key-clicks using piezoelectric actuators, it was found that changing the amplitude and the number of cycles (up to 3, so as to avoid the undesirable "ringing" sensation) of a sinusoidal driving signal led to a change in the overall perceived intensity of the simulated key click. When participants were asked to identify the amplitude, frequency, and number of cycles in a simulated key-click signal, a significant number of errors were associated with the participants' judging a multiple-cycle signal as having a higher amplitude than that presented (see [51, Exp. III and Table 6]). This indicates that the two independent physical variables of signal amplitude and number of cycles merged into one perceptual dimension of perceived intensity. Therefore, whereas in many cases the physical and perceptual dimensionalities may be the same, there also exist ample examples where the two are not equal.

Why is it important to know the number of perceptual dimensions associated with a stimulus set, and how should one go about discovering the perceptual dimensionality if one suspects that the physical and perceptual dimensions are different?

The theme of this article is to maximize the information transmission of human–machine interfaces. We know that the IT for any unidimensional stimulus is limited by the "magic number 7 ± 2." By employing multidimensional stimuli with an interface system, it is possible to increase the perceptual dimensions involved and achieve an IT that is more than the "magic number." That is why it is very important to know the number of perceptual dimensions associated with a stimulus set. However, how much IT can be increased by employing multidimensional stimuli depends on the perceptual independence of the dimensions. Many definitions of perceptual independence exist. For the purpose of our discussion, we define perceptual independence similarly as separability: "With separable stimulus components, performance on a task that demands a response based on a single component is unaffected by the level of other irrelevant components. With integral components, varying the level of irrelevant components degrades performance" (see Operational Definition A in [52, p. 163]). In other words, if two perceptual dimensions are separable/independent, then the IT for both dimensions equals the sum of the IT for each dimension. The more integral/dependent the two dimensions are, the less gain in IT can be had by employing both dimensions in a stimulus set. Interestingly, redundant coding with two or more dimensions that vary in correlation can result in increased IT even though the information in stimulus remains the same. The estimation of multidimensional IT is discussed in detail in Section II-D.

One way to judge whether one physical variable can lead to more than one perceptual dimensions is to apply the test given in the definition of separability and integrability. In the example given earlier where varying the frequency of sinusoidal stimuli leads to three distinct sensations of motion, flutter, and vibration, the existence of the additional perceptual dimensions was demonstrated by combining single-frequency sinusoidal signals from the low-, mid-, and high-frequency regions and showing that each component remained perceptually distinct upon stimulus reception. Another way to discover the perceptual dimensions associated with a stimulus set is to conduct a multidimensional scaling study, especially when the physical dimensionality associated with the stimuli may be ill-defined (such as surface texture and haptic simulation of key clicks) [53]–[56]. A detailed discussion of the multidimensional scaling technique is beyond the scope of this article. The readers are advised to determine the perceptual dimensionality of a stimulus set judiciously.

Note that the concept of channel capacity for unidimensional stimuli does not apply to "overlearned" stimuli. For example, individuals with absolute or perfect pitch can identify all 88 notes on a keyboard perfectly when any single key is struck without a reference note.

In addition to increasing the number of dimensions as a means to increase total IT, channel capacity can also be expanded by increasing the amount of information contained in each item through chunking or recoding, the process of learning to recognize a sequence of stimuli as a single item [31]. A good example is how ham radio operators can code dit-dah patterns into letters, then into words and then into short phrases as they become more experienced. Even though the number of sequentially presented items one can correctly recall is also limited to about seven [31], the total information transmission can be expanded by increasing the information per item through chunking.

C. Practical Issues in the Estimation of Channel Capacity

It should now be clear that in applications where the correct identification of signals is important for the successful execution of a task, and we are interested in the estimation of channel capacity that can quantitatively guide us in designing a distinctive set of signals. In order for the IT from an absolute identification experiment to be a good estimate of channel capacity, six important issues need to be taken care of. First, one should use the entire range of each physical parameter that is varied to generate the stimuli. Second, the number of stimulus alternatives (K) needs to be sufficiently large. Third, the total number of trials needs to be at least $5K^2$ in order to overcome the statistical bias in $\mathrm{IT}_{\mathrm{est}}$, the maximum-likelihood estimate of IT [30]. Fourth, it is preferred that the method of randomization with replacement be used in selecting stimulus alternatives on each trial. Fifth, the K stimuli should preferably be spaced such that each adjacent pair of stimuli is equally discriminable. Last but not least, the response labels should be intuitive or easy to learn, and sufficient training should be provided to ensure that the participant is familiar with the stimuli and the associated response labels. The rest of this section discusses each issue in detail.

IT increases initially and then plateaus as the range of stimuli increases. Replacing the abscissa in Fig. 3 with stimulus range produces a similar graph, according to models and experimental data on auditory intensity perception [40], [41], [57]. The effect of range has been demonstrated for haptic perception in a length identification experiment using the finger-span method [44]. It thus appears prudent that the whole range of stimulus parameters be employed in an absolute identification experiment, so as not to underestimate channel capacity due to the effect of stimulus range.

Similarly, as shown in Fig. 3, IT increases initially and then plateaus as the number of stimulus alternatives increases. This trend has been explicitly tested in the length identification experiment [44] and clearly demonstrated in a sphere size identification task using hemispheres rendered with a force-feedback device [34]. The trick, however, is how to select a reasonable value of K for the number of stimulus alternatives. In many psychophysical paradigms, the proper selection of stimulus parameters may depend on some prior knowledge of what the experimental outcome might be. In this case, the experimenter needs to take an initial guess of the channel capacity and then pick a K or IS value that is slightly larger. During the absolute identification experiment, the experimenter needs to ascertain that the participants are not performing perfectly (i.e., the point being tested is on the plateau, not the linear portion of the curve in Fig. 3). For reasons that will become clear in the next paragraph, it is not advisable to pick a K or IS value that is too large. We also hasten to point out that the percent-correct score in an absolute identification experiment is not a good way to characterize performance as it continues to drop as the task difficulty (i.e., K) increases. In contrast, IT plateaus and provides a more parsimonious measure of human performance in terms of channel capacity.

An issue that is often overlooked in the literature is the number of trials needed in order to obtain an unbiased estimate of channel capacity. $\mathrm{IT}_{\mathrm{est}}$ in (3) is statistically biased in the sense that its expected value $E[\mathrm{IT}_{\mathrm{est}}]$ is greater than the IT value as shown in (2)

$$\begin{aligned} E[\mathrm{IT}_{\mathrm{est}}] - IT &= \frac{\log_2 e}{2n}(K-1)^2 + O\left(\frac{1}{n^2}\right) \\ &= \Delta + O\left(\frac{1}{n^2}\right) \end{aligned} \tag{5}$$

where n is the total number of trials and $O(1/n^2)$ represents the higher order terms [30]. When $n = 5K^2$, the bias $\Delta = 0.14$ bit is relatively small and can be neglected. When n is significantly smaller, it was suggested that Δ be subtracted from $\mathrm{IT}_{\mathrm{est}}$ to correct for the bias [30]. The possibility of overestimating IT is usually not a problem with unidimensional stimuli, because even for $K = 8$, the required $5K^2 = 320$ trials is still quite manageable. For multidimensional stimuli, however, the numbers can add up quickly. For example, a 3-D stimulus set employing five levels of vibratory intensity, five levels of frequency, and five levels of contactor area leads to a K of $5 \times 5 \times 5 = 125$ and a $5K^2$ of 78 125 [58]. A total of 5000 trials was collected from the 3-D absolute identification experiment, and computer simulations were run to extend the number of trials from 5000 to 25 000. By fitting the experimental data with simulated data, a channel capacity of around 4 bits was extrapolated for the 3-D stimulus set [59]. Interestingly, the same plot also demonstrated clearly how the application of Miller's [30] bias correction Δ resulted in an overcorrection of estimated IT. Two of us have tried using Houtsma's [59] simulation for prediction of unbiased IT. One of us was successful [60] (see also the end of Section II-B). The other could not match the shape of the experimental data in terms of estimated IT as a function of number of trials to any of the simulated curves (unpublished results, using data in [10]). Therefore, even though one might be able to make use of the correction term Δ suggested by Miller [30] or the computer simulation by Houtsma [59] to counteract the overestimation in $\mathrm{IT}_{\mathrm{est}}$ in some cases, neither method works robustly for all experimental data. To the best of our knowledge, it is still best to collect a sufficient number of $5K^2$ trials whenever possible. In cases of multidimensional stimuli with a large K and a potentially high IT, we discuss an experimental approach for estimating potentially high channel capacity based on a general additivity law explained in Section II-D.

Another issue that is often overlooked and not explicitly reported in the literature is the way stimulus sequences are generated in an absolute identification experiment. It is very common for each stimulus alternative to be presented an equal number of times. On each trial, one of the stimuli is randomly selected. If the chosen stimulus has already been presented for the maximum number of times, another stimulus is randomly chosen. This method, termed randomization without replacement, has the advantage that the participant is exposed to each stimulus an equal number of times. It, however, has the disadvantage of a decreasing IS as the trial number increases, as can be seen from (4). In order to ensure that IS remains constant throughout an experiment, the method of randomization with replacement should be used, where each stimulus alternative has an equal probability of being presented on each trial. The consequence is that each stimulus alternative may have a different number of presentations. This, however, should not be a problem with a sufficient number of trials.

The spacing between adjacent pairs of stimuli in an absolute identification experiment should ideally be equal in the perceptual space. In cases where Weber's law applies, the just noticeable difference (JND) is proportional to the reference signal. For example, assuming a JND of 10% for force–magnitude perception [61], [62], the two force–magnitude pairs of 5.0 and 5.5 N and 10.0 and 11.0 N are equally discriminable. Therefore, a force–magnitude identification experiment should select force levels that are equally spaced on a logarithmic scale (e.g., 0.1, 0.2659, 0.7071, 1.8803, and 5 N as was the case in [46]). When it is unknown whether the perception of a variable follows Weber's law, it is more difficult to determine the optimal placement of multiple stimuli within a parameter range. Luckily, channel capacity does not appear to be affected by the stimulus spacing, at least for length identification [44] or sphere size identification [34]. Therefore, we recommend that stimuli be equally spaced on a logarithmic scale if Weber's law holds and otherwise on a linear scale.

Training and stimulus–response compatibility are integral parts of a well-designed absolute identification experiment. Typically, the participants need to be familiar with the multiple stimuli presented and the response labels used to identify them. Prior to data collection, the experimenter should provide an easy-to-use interface for the participant to try any one of the stimulus alternatives for 5–15 min, or until the participant is ready. The design of response labels should support stimulus–response compatibility and be as intuitive as possible. There is a vast literature on stimulus–response compatibility, which is beyond the scope of this article. In cases where a large number of multidimensional stimuli is employed, a graphics-based response method can be used.

For example, the participants in the Tactuator study [10] used a stylus to select graphic icons on a digitizing table to respond to a 120-alternative stimulus set (see Fig. 4). The participants, who were mostly engineering students, were told that the stimuli were specified by frequency in hertz and intensity in decibels. For example, (2, 35) indicated a 2-Hz movement at an intensity of 35-dB sensation level (SL; i.e., decibel above human detection threshold at this frequency). They learned that the icons for the eight single-frequency signals occupied the first column and continued on the bottom row. It was easy to see that these icons contained waveforms that represented the relative frequencies and amplitudes of the stimuli, with the exception that the 150- and 300-Hz signals were represented in blue and red colors, respectively. The second

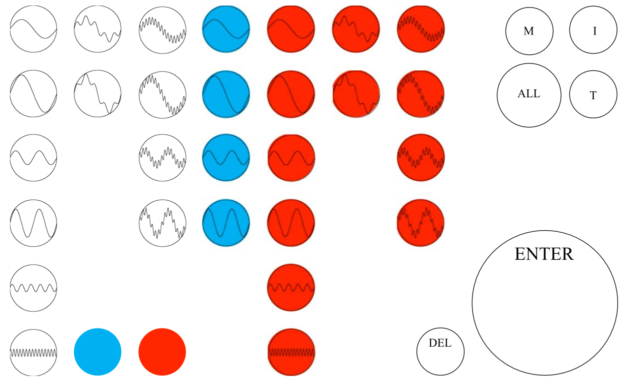


Fig. 4. ***Graphics-based response tablet using spatial layout to group signals with one-, two-, and three-frequency components applied to a single or multiple digits of the hand. Modified from Fig. 3 by Tan et al. [10].***

icon on the top row represented the combination of (2, 35) and (10, 35). The third icon represented (2, 35) and (30, 40), etc. It was apparent that all icons on the top row contained a (2, 35) slow-movement component. That way, the 30 waveforms were laid out in an organized manner and easy to locate for the participants. In the upper-right corner of Fig. 4, the "M/I/T" icons were laid out in a spatially congruent manner with the locations of the middle finger, index finger, and the thumb of the left hand. The "ALL" icon was for when all three digits were stimulated and was slightly larger in size. The participants selected one location icon and one waveform icon to respond to each stimulus presentation. The large "ENTER" icon was used to confirm a response and to advance to the next trial, while the small "DEL" icon was available for deleting a previously entered icon. The design of the response codes shown in Fig. 4 provides a good example of how to maximize stimulus–response compatibility and minimize response errors in an absolute identification experiment involving a large number of stimulus alternatives.

D. Estimation of Multidimensional Channel Capacity and a General Additivity Law for IT

As mentioned earlier in Section III-B, channel capacity for any unidimensional stimuli is limited. However, higher IT can be achieved by employing multidimensional stimuli. It follows that for any interface with high information transmission capacity, its channel capacity has to be assessed with an absolute identification experiment with multidimensional stimuli. The problem, as mentioned in Section III-C, is that the total number of stimulus alternatives (K) grows exponentially as the number of dimensions increases. This in turn makes it very time-consuming, if not impossible, to collect a sufficient number of trials ($5K^2$) in order to obtain an unbiased estimate of IT.

Durlach *et al.* [63] addressed the question of whether a multi-D IT can be predicted from the sum of 1-D ITs estimated with each of the dimensions making up the stimulus set. In general, IT(multi-D) $<$ $\sum$IT(1-D) due to perceptual interferences among the stimulus dimensions [28], [52]. Let us examine the way that a 1-D absolute identification experiment is typically conducted, say, for vibratory stimuli. To assess the channel capacity for perceived intensity, the stimuli would consist of sinusoidal vibrations at multiple amplitude levels and one fixed frequency. This is called an absolute identification experiment with fixed background. The IT so obtained does not take into account the effect of frequency on intensity perception. For example, it is well known that the vibrotactile skin-displacement detection threshold is lowest around 200–300 Hz [64]. Therefore, a 250-Hz vibration feels stronger than a 25-Hz vibration with the same (physical) displacement amplitude. The dependence of haptic intensity perception on frequency would lead to a lower channel capacity if the frequency of the stimuli were randomized from trial to trial, the so-called roving background paradigm. More generally, for a multidimensional stimulus set with M dimensions, the participant is asked to identify the target dimension while the levels of the $M - 1$ background dimensions vary from trial to trial. The 1-D ITs obtained with a roving background are likely to reflect the decreases in channel capacity due to perceptual interference and integrality. Their sum can therefore be a reasonable estimate of the multi-D IT. This was the main idea behind the general additivity law for IT proposed by Durlach *et al.* [63].

Since its publication, the general additivity law has been demonstrated with the experimental data where 1-D ITs with fixed background, 1-D ITs with roving background, and multi-D IT are estimated and compared [33], [51], [65], [66]. For example, Chen *et al.* [51] measured 1-D ITs with fixed and roving background, and compared their respective sums to the 3-D IT obtained from a 3-D identification experiment. To make it tractable to collect a sufficient number of trials in the 3-D identification experiment, they used the results of the 1-D identification experiments to pare down the number of alternatives in the full stimulus set. In this way, Chen *et al.*'s [51] experiments were designed to guide the development of a final set of perceptually distinct stimuli (in this case simulated key-click signals), and at the same time verified the general additivity law proposed by Durlach *et al.* [63].

Since it takes many more trials to collect a sufficient number of trials for one M-dimensional absolute identification experiment than those required for M 1-D identification experiments, it generally takes less trials to estimate the multi-D IT by the sum of 1-D ITs. Therefore, the general additivity law proposed by Durlach *et al.* [63] can lead to significant savings in the experimental time required to obtain unbiased estimates of multi-D ITs. The key is to conduct the 1-D absolute identification experiments with a roving background.

E. Estimation of IT Rates

Until now, this tutorial has focused on the estimation of static IT, for unidimensional and multidimensional stimuli. The tutorial would not be complete without a discussion on how to conduct experiments to estimate the IT rates that can be achieved with a 1-D or multi-D stimulus set. The concept of IT rate is important because it addresses the issue of how quickly, in addition to how accurately, information is transmitted through communication devices. Tan *et al.* [35] reviewed the literature on IT rate from the 1950s to early 2000s, from the perspective of what determines the optimum IT rate. They discussed the many factors that affect one's performance in an IT rate experiment as compared to those in a static IT experiment. First, the participants need to be sufficiently trained so that the time required to respond to each stimulus in a sequence is minimized, assuming that the stimulus alternatives are distinct and stimulus–response compatibility is high. Second, there are both forward and backward masking effects when stimuli are presented in a sequence as opposed to in isolation. The term masking refers to a reduced ability to perceive a stimulus in the presence of another stimulus that occurs in close temporal or spatial proximity. Third, there is the demand on sustained attention and memory that is associated with responding to a sequence of stimuli, especially when the act of responding lags behind stimulus presentation. For these reasons, a full-blown IT rate experiment where the participants are asked to respond to a stimulus stream continuously is often impractical within the typical time frame of a research study, except for overlearned stimuli such as speech.

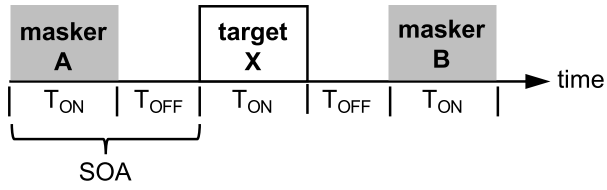


Fig. 5. ***Illustration of the AXB masking paradigm for estimating IT rate. Modified from [10, Fig. 6].***

Tan *et al.* [10], [35] recommended an AXB paradigm where the participant is required to identify only the middle stimulus (X) in a sequence of three consecutive stimuli (AXB), as depicted in Fig. 5. This experimental paradigm allows IT rates to be estimated within a reasonable time while simulating to some degree the effects of forward (from stimulus A) and backward (from stimulus B) masking on stimulus X. All three stimuli have the same signal duration (T_{ON}) and equal interval of silence (T_{OFF}) between them. The signal onset asynchrony (SOA) is simply $T_{ON} + T_{OFF}$. On each trial, the target stimulus X, the forward masker A, and the backward masker B are selected randomly from the alternatives within the same stimulus set. Performance can be observed as a function of decreasing T_{OFF} (typically over a range of 1000–0 ms). Estimates of IT rate in bits per second for each SOA is calculated from the product of the IT per presentation in bits/item and the presentation rate in items/s (i.e., the reciprocal of SOA).

III. METHODS AND MAJOR FINDINGS OF LITERATURE SURVEY

As summarized in Section II, the information-theoretical framework offers a well-established theory for objective and context-free comparisons of the information processing capacity of sensory displays. It has been used by haptics researchers to evaluate the communication performance of various devices and rendering algorithms. Our search for research articles that report IT values of haptic systems resulted in 35 relevant studies. They generally include development of haptic interfaces or design of haptic stimuli for effective man–machine communication. We tabulated the spatial, temporal, and intensive characteristics of the haptic stimuli designed and used for the estimation of IT for each of the studies. This allowed us to make observations of the effectiveness of individual physical and perceptual dimensions used in the stimulus design for improving communication bandwidth.

For haptic perception, there is a unique neurological mapping between a body site and the corresponding cortical area in the brain that processes the transmitted signal [67]. While stimulating a single site on the skin is technically simpler, multichannel tactile stimulation using a number of tactors applied to different body locations can generally improve human haptic information processing to a great extent. Furthermore, multiple stimuli can be delivered either simultaneously or sequentially, and this vastly enlarges the design space of haptic stimuli. In particular, certain temporal stimulus sequences can elicit the illusion of movement; for example, a few discrete tactile stimuli applied at different locations are perceived to be one continuous stimulus moving along the skin surface [68]. Tactile motion illusions have been frequently used in haptic system design and applications. In addition, each individual tactile stimulus can vary along many dimensions such as amplitude, frequency, duration, rhythm, roughness (e.g., through signal modulation), contact area, and contact location. In the rest of this section, we review the 35 articles collected in the literature survey with an eye toward the roles played by various haptic stimulus dimensions in information transmission. We organize the subsections by vibrotactile, force-feedback, and other types of haptic displays. Within vibrotactile displays, we discuss separately stimuli that use or do not use tactile movement illusions.

We note that few of the 35 studies reported IT rates and the results tended to be quite unimpressive (e.g., 2.7–2.9 b/s in [69]; although see [35, Fig. 2(b)] and [60] that show much higher IT rates). Thus, our review focuses on specifying and comparing IT values instead of IT rates.

A. Information Transmission With Stimuli That Do Not Use Movement Illusions

Studies of haptic information processing capacity using an information-theoretical framework date back to the 1980s. The dimensions studied include vibrotactile frequency, amplitude, duration, and body location, which have clear physical definitions, as well as roughness and rhythm, which are perceptual dimensions affected by multiple physical variables. In general, the use of multiple dimensions with only a few parameter values per dimension has been effective at achieving high information transmission capacity. However, care should be taken when combining multiple dimensions to minimize perceptual interferences among the dimensions. The two most successful cases of following the above guidelines are a tactile belt with an IT of 4.18 bits by Barralon *et al.* [70] and a multifinger display (the Tactuator by Tan and Rabinowitz [71]) with an IT of 6.50 bits [10], the highest IT ever reported in the literature for haptic stimuli that do not use tactile movement illusions.

Using a piezoceramic bender bimorph on a fingertip, Sherrick [72] estimated an IT value of 2.23 bits for the identification of frequency alone, and 2.67 bits for the identification of co-varying frequency and intensity values, demonstrating the effectiveness of redundant coding in increasing IT. Rabinowitz *et al.* [58] applied vibrations to the distal pad of the middle finger using an array of electrodynamic actuators mounted on a rotating disk. They estimated 1-D IT values for the identification of vibration intensity, frequency, and contact area, and found an average 3-D IT to be 4.0 bits when the three stimulus parameters varied independently. The 3-D IT value corresponds to 16 ($2^{4.0}$) perfectly identifiable vibration patterns, demonstrating a higher IT with a larger number of perceptual dimensions in the stimulus set. Under a similar setup, Summers *et al.* [73] varied the frequency, amplitude, and waveform of vibrotactile stimuli and obtained a 3-D IT value of 1.0 bit. This lower 3-D IT is presumably due to the lack of separability among the three dimensions.

The Tactuator by Tan *et al.* [10] and Tan and Rabinowitz [71] was perhaps the first multifinger tactual display designed to maximize information transmission. Inspired by the Tadoma method of speech communication where the hand of the "listener" has access to a talking face with rich, multidimensional information associated with the articulatory processes, the Tactuator delivered kinesthetic movements (large amplitude, low frequency) and vibrations (low amplitude, high frequency), as well as fluttering/rough stimulation (mid-amplitude, mid-frequency) to the distal pads of the thumb, index, and middle fingers (see Fig. 6). The signal waveforms contained only two frequency levels per frequency region (low, mid, and high) and no more than two intensity levels per frequency. Single-frequency signals from different frequency regions were combined to form two- and three-frequency signals that were readily identifiable due to the distinctiveness of each frequency component. For example, a 2-Hz motion combined with a 300-Hz vibration was perceived to be a slow motion with superimposed smooth vibration.

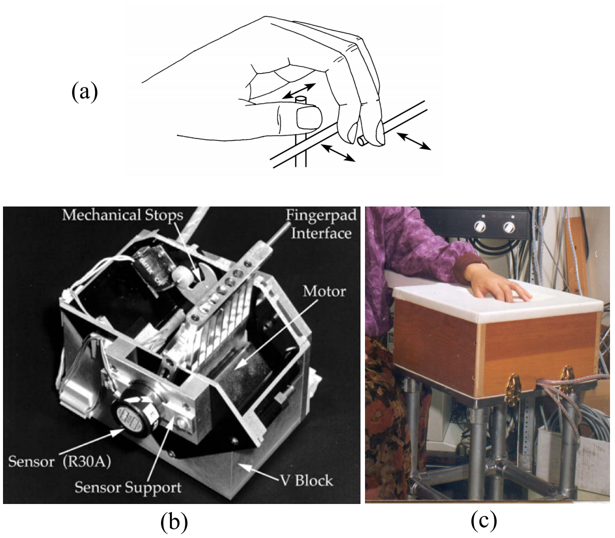


Fig. 6. ***Tactuator. (a) Illustration of finger placement and motion trajectories (from [71, Fig. 1]). (b) Motor assembly for the middle finger (from [71, Fig. 4]). (c) Exterior view of the Tactuator system.***

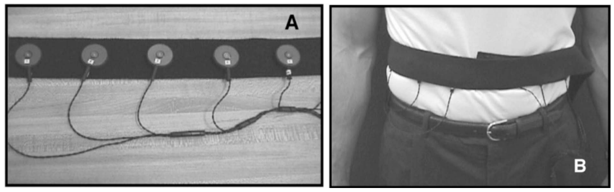


Fig. 8. ***Common arrangement of tactors around the waist (from [80, Fig. 3]). (a) Five tactors attached to a Velcro belt. (B) Tactile belt worn around the waist.***

A total of 30 stimulation patterns containing eight single-frequency, 16 double-frequency, and six triple-frequency signals were delivered to either one of the three digits or all of them (i.e., four possible stimulation locations), resulting in a stimulus set containing 120 alternatives. Estimated IT was 6.50 bits, corresponding to an impressive 90 distinctly identifiable stimulation patterns.

Since the Tactuator, various tactile displays have been developed to stimulate the body using multiple actuators. The review that follows is organized with respect to the form factors that largely determined the body locations that were stimulated.

It was most common to find vibrotactile stimuli presented to the finger(s), wrist, or arm, often with tactors in an array. For example, Chen *et al.* [74] used a 3×3 array of linear resonance actuators to investigate tactor localization performance at the wrist (see Fig. 7). The estimated IT was 1.00 bit when the array was attached to the dorsal side of the wrist and 1.24 bits for the volar side, confirming a better resolution of the volar skin. When two 3×3 arrays were placed on both the dorsal and volar sides of the wrist, IT increased to 1.99 bits with the additional dimension. Similarly, Sofia and Jones [75] used a 3×3 array of vibration motors and estimated tactor localization IT to be up to 2.46 bits on the palm, 1.42 bits on the forearm, and 1.32 bits on the thigh, following an expected decreasing trend. Cholewiak and Collins [76] applied an array of custom-designed piezoceramic benders to the forearm and upper-arm. The IT value for tactor localization was 1.28 bits on the forearm (excluding wrist and elbow), up to 1.45 bits on the forearm (including wrist and elbow), and 1.67 bits on both the forearm and upper-arm (including wrist and elbow). These results stressed the importance of having natural anchor points close to joints for improved localization. Wong *et al.* [77] designed a sleeve with six vibration motors along the longitudinal direction of the forearm, and achieved up to 1.84 bits for localization. The aforementioned studies all employed tactor location as the only stimulus dimension. The IT for tactor localization on the upper extremity appears to be limited, with the highest value on the palm (2.46 bits) that corresponds to about five distinct locations. A similar IT value of 2.41 bits was reported by Azadi and Jones [78], with vibrotactile stimuli that varied in multiple dimensions, such as frequency, amplitude, duration, and temporal profile (pulses), but not location, on either the index fingertip or forearm. A higher IT was achieved when location as well as stimulus properties were used to convey information. Brown *et al.* [79] attached three voice coil actuators on the forearm and designed and tested multidimensional tactile icons called “tactons” by varying rhythm, roughness, and locations. The reported IT value was 2.98 bits. It thus appears that the channel capacity for vibrotactile array placed on the upper extremity does not exceed 3 bits (or eight distinct tactons).

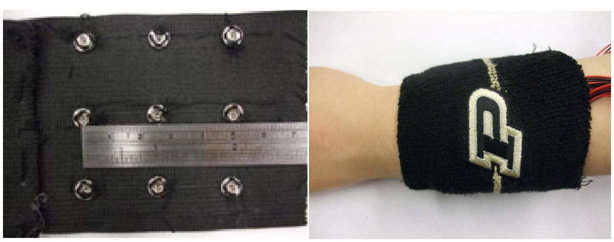


Fig. 7. ***Typical configuration of tactor arrays worn around the wrist or arm (from [74, Figs. 1 and 2]). (Left) 3×3 tactor array (tactor diameter 8.5 mm) with an interelement spacing of 25 mm. (Right) Tactor array wrapped around the wrist using a Velcro band.***

Other body sites such as the waist and torso are also good candidates for receiving stimulation from a tactor array. As shown in Fig. 8, Cholewiak *et al.* [80] designed a belt with an embedded array of voice coil actuators and reported an IT of 2.66 bits for tactor localization performance. This article was extended by Cholewiak and McGrath [24] by building a 4×6 tactor array that was wrapped around the torso and increased IT for localization to 2.98 bits. Barralon *et al.* [70] increased the IT to

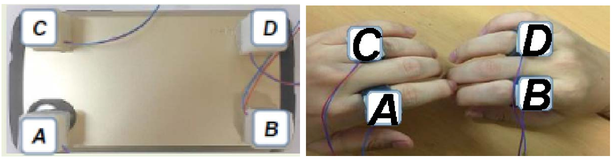


Fig. 9. *Four linear resonance actuators (LRAs) attached to the corners of a smart phone (left, PHONE configuration) and four rings worn on the index and ring fingers of both hands (right, RING configuration). Modified from [60, Fig. 6] that used the same apparatus as mentioned by Park and Choi [82].*

4.18 bits by varying the vibrotactile stimuli sent to a tactor array on a tactile belt along the dimensions of rhythm, roughness, and location. These results again advocate for combining tactor localization with the parameters of vibrotactile stimulation signals to increase the number of dimensions for increased IT and demonstrate a maximum IT of 4.18 bits (18 distinct vibrotactile patterns) on the torso.

Another way to stimulate the hand is through vibrotactile feedback on mobile devices. Ryu *et al.* [81] proposed a method to apply tactor driving voltage levels that resulted in linear changes in perceived vibration intensity. They demonstrated an IT increase in intensity identification from 1.23 to 1.68 bits with the improved spacing of stimulus intensities. Chen *et al.* [51] studied identification of key-click sensations simulated with a piezoelectric actuator in a mobile phone. They reported a 3-D IT of 2.4 bits by varying vibrotactile frequency, amplitude, and duration (number of cycles) independently, a result that is consistent with the expectation of increased IT with increased dimensionality.

In a unique study that utilized the funneling illusion, Park and Choi [82] estimated the IT for localization of phantom sensations. Their study used the funneling illusion, an illusory tactile sensation that occurs when multiple tactile stimuli are brief in duration, delivered simultaneously, and in close spatial proximity. A single "phantom" point of stimulation is perceived at the geometric center if the stimuli are of equal intensity or in the direction of the more intense stimulus [83]. Four modules (each containing a tactor and a silicon layer for vibration isolation) are placed either at the four corners of a mobile device (PHONE configuration) or worn on the index and ring fingers of two hands (RING configuration) (see Fig. 9). The IT value was up to 1.89 bits with the PHONE configuration and 2.53 bits with the RING configuration. Interestingly, the phantom sensations with the RING configuration were perceived outside of the body in the empty space between the two fingers under stimulation. Localization of the illusory sensations was the best with a 3×3 grid that included the four tactors in the RING configuration (Fig. 9, right-hand side) as the outer corners and five phantom loci between pairs of the tactors (e.g., midway between A and B, or between A and D). The use of higher-resolution virtual grids (4×4 or 5×5) bounded by the same four tactors led to lower IT values. It was intriguing that the out-of-the-body phantom sensations arising from the RING configuration resulted in a higher IT value than that from the within-the-body phantom sensations with the PHONE configuration.

Finally, Horvath *et al.* [84] developed a wearable system called FingerSight (see Fig. 10) that converted an image from a camera mounted on the tip of an index finger to a vibrotactile signal rendered on the corresponding fingertip. Their edge rendering algorithm showed an angle identification performance of up to 1.62 bits. This system is unique due to its interactive nature, and the relatively low IT value may be attributable to factors other than the channel capacity of haptic perception.

B. Information Transmission With Stimuli That Use Movement Illusions

The results that have been discussed up to this point with stimuli that do not use movement illusions support the use of multiple dimensions for increased IT, although it is evident that not all dimensions contribute equally. The best result of 6.50 bits obtained with the Tactuator supports the use of a broad frequency range in constructing the stimulus set [10]. The Tactuator is unique in that it presents both kinesthetic (low-frequency motions) and tactile (vibrations) stimuli to users whereas most of the other studies reviewed in this article present only vibrotactile stimuli. The next best result of 4.18 bits obtained with a tactile belt supports the use of multiple tactor locations as an effective additional dimension [70]. In this section, we examine the efficacy of another effective perceptual dimension associated with the use of tactile movement illusions.

A temporal sequence of tactile stimuli applied to different body sites can induce a movement illusion on the body. Three types of tactile illusions have been frequently used: apparent motion, sensory saltation, and funneling illusion [68]. Apparent motion is characterized by an illusion of a single point moving smoothly on the skin surface. It can be induced by activating a number of tactors in a

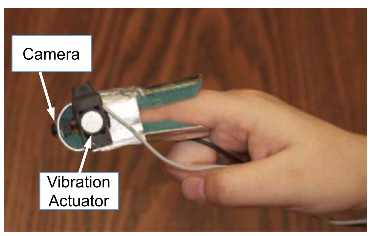


Fig. 10. *FingerSight device (modified from [84, Fig. 4]). Visual information is captured using a camera in front of the fingertip when the user scans a surface. The visual information is processed to provide appropriate tactile feedback, e.g., for visual edges, to the finger using a vibrotactile actuator.*

temporal sequence. The optimal SOA (time between the onset of two subsequent vibrations) was experimentally determined to be $0.32^*d + 47.3$ ms where d denotes the vibration duration in ms [85]. Typically, the first tactor is still on when the next tactor starts, creating an overlap in activation that is important for the perceived smoothness of the movement illusion. It has been shown that the apparent motion illusion can create straight and curved movement trajectories on various body sites such as the back and the palm [86], [87]. Sensory saltation, also known as the "cutaneous rabbit," is qualitatively different from the apparent motion in that an illusory saltatory locus "hops" across the skin. It is induced by several short, nonoverlapping pulses delivered through one tactor, followed by the same through a second tactor, and so forth. For sensory saltation to occur, the intertactor distance on the back should be less than 10 cm, the optimal number of taps are between 3 and 6, the optimal gap between pulses is 20–250 ms, and the intensity and duration of pulses are of secondary importance [26], [88]–[91]. It has also been shown that a series of taps along a linear trajectory generated by veridical and saltatory presentations lead to equivalent sensations [90], thus a perceptually higher spatial resolution can be achieved with a sparse array of tactors. As mentioned earlier, the funneling illusion refers to the mislocalization of brief tactile stimuli delivered simultaneously to two closeby points on the skin as a single stimulation point between the two stimulated points [83]. A gradual change of the relative vibrotactile intensities at the two points can create an illusion of a moving point on the skin. As far as we are aware, Park and Choi's [82] was the only study that investigated IT using phantom loci. We have not come across any other study that characterized IT using illusory movement generated by the funneling illusion.

In the rest of this section, we review tactile displays featuring illusory movement sensations and their information transmission capacities. Similar to Section III-A, the related work is organized with respect to the target body sites of the tactile displays.

Hsieh *et al.* [92] designed NailTactors with four vibrotactile motors mounted around a fingernail to render moving spatiotemporal patterns as shown in Fig. 11. An IT of 2.71 bits was obtained for the identification of the ten numerical digits "drawn" with NailTactors. Culbertson *et al.* [93] made use of asymmetric vibrations using a voicecoil actuator that delivered a pulling sensation in one direction. When attached to the fingers, a single voicecoil actuator presented a translational guidance cue, and a pair of voicecoil actuators generated a rotational guidance cue. Using three actuators worn on the thumb, index finger, and middle finger, the estimated IT was 2.04 bits for the identification of translational cues and 1.70 bits with rotational cues. These results show an IT of up to 2.71 bits on the fingers.

Matscheko *et al.* [94] placed four voice coil actuators on the wrist in a configuration of "face" (tactors arranged like a wrist-watch face) and "wrist" (tactors around the wrist), and obtained an IT of 1.90 and 2.49 bits, respectively, for the recognition of rotational patterns designed for the two configurations. Lee *et al.* [95] used a 3 × 3 tactor array placed on the wrist to present spatial patterns including points, lines, and saltatory movements, and obtained an IT of up to 1.64 bits. Lee and Starner [96] designed Buzz-Wear, in which three vibrotactile motors were wrapped around the wrist to deliver 24 rotational vibration patterns that varied in intensity, temporal pattern, duration, starting point, and movement direction (see Fig. 12). The IT for pattern identification was 4.28 bits despite the small number of tactors used [96]. Liao *et al.* [97] used four vibrotactile motors on the back of a wrist watch to represent English letters and numerical digits using spatiotemporal vibration patterns, and achieved an IT of 4.31 bits for letter and digit recognition. The relatively high IT values achieved on the wrist, 4.3 bits (19 patterns), support the use of spatial and spatiotemporal patterns for effective information transmission.

Jones *et al.* [98] conducted a series of experiments to evaluate the effectiveness of a 3 × 3 tactile array mounted on the forearm and a 4 × 4 array on the back for communicating simple messages using spatiotemporal patterns that represented navigation and orientation commands (see Fig. 13). The IT values were up to 2.15 bits on the forearm and 2.68 bits on the back. Israr *et al.* [86] designed a chair back with a 2 × 3 voice coil array to improve the viewing experiences of 360° videos. The IT for

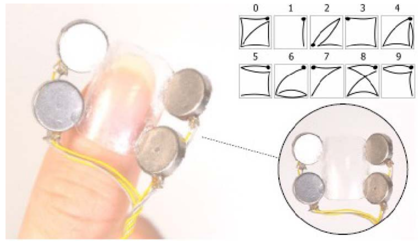


Fig. 11. ***NailTactors. Nail-mounted tactile display with four vibrotactile motors (from [92, Fig. 1]). The vibrotactile movement patterns shown at top-right represent digits.***

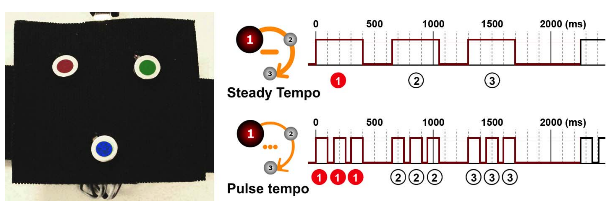


Fig. 12. ***BuzzWear [96, Fig. 1]. (Left) Wristband with three motors worn on the volar side of the wrist. (Right) Examples of vibration patterns. (Top) Pattern that starts at tactor 1 and moves in the clockwise direction with one continuous vibration per tactor. (Bottom) Similar pattern with three pulses per tactor.***

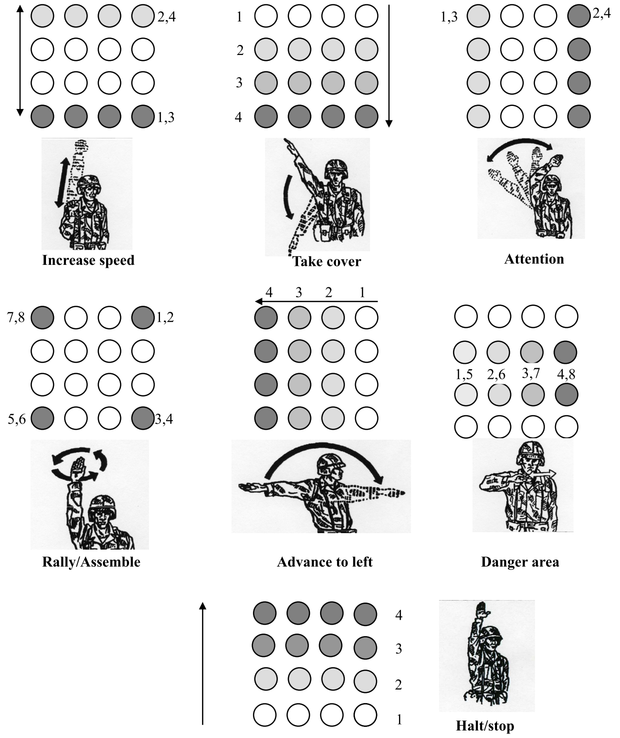


Fig. 13. ***Vibrotactile patterns representing military hand signals (modified from [98, Fig. 4]). Arrows indicate the moving directions of spatiotemporal vibrotactile stimuli.***

identification of moving stroke patterns was 2.55 bits [86]. The IT results on the forearm and back were less remarkable as those obtained on the wrist.

Similar IT results were obtained with mobile devices. Yatani and Truong [99] embedded five tactors in a thick sponge (for vibration isolation) that covered the backside of a mobile phone. The IT for the identification of one-actuator signals and linear and circular spatiotemporal patterns was 2.80 bits [99]. Seo and Choi [100] affixed four actuators at the four corners of a rectangular mobile device and developed a rendering algorithm for "edge flows," which refers to the sensations of continuously moving tactile stimuli following the edges of a rectangular mobile device. Identification of edge-flow patterns resulted in an IT of 3.70 bits.

The highest IT values for stimuli that use movement illusions were reported by Park *et al.* [60] who developed small vibrotactile modules that could be attached to and detached from devices such as mobile phones and game consoles (see Fig. 9 for the PHONE and RING configurations). A large number of distinctive tactile stimuli were designed by varying signal durations (100 and 250 ms), the number of vibrations (1–4), and the locus sequence of spatiotemporal patterns (e.g., B→A, A→D→C). An absolute identification experiment showed an IT value of 6.88 bits with the PHONE configuration and 7.02 bits with the RING configuration. As mentioned in Section II-C, the maximum likelihood estimate of IT is biased toward an overestimation when the total number of trials is insufficient. This is likely to happen when the number of stimulus alternatives is large. To address this concern, Park *et al.* [60] carried out an additional analysis on the biases in IT estimation with the PHONE and RING configurations. They obtained the following lower-bound IT values using the simulation-based method presented by Houtsma [59]: 6.67 bits (compared to 6.88 bits) for the PHONE configuration and 6.89 bits (compared to 7.02 bits) for the RING configuration. The relatively small corrections in IT were likely due to the distinctiveness of the stimuli used and the high performance levels (i.e., few errors were observed and hence no need for a large number of trials for the proper estimation of the error patterns in the stimulus-response confusion matrix). To the best of our knowledge, these are the highest IT values that have been reported in the tactile communication literature.

In summary, when movement illusions were employed in addition to vibrotactile frequency and duration with tactor arrays, ITs for vibrotactile pattern recognition increased significantly to impressive values: around 4.3 bits (19 patterns) on the wrist with three or four tactors [96], [97], and 7.0 bits (130 patterns) for RING with four tactors worn on the index and ring fingers of two hands [60], [101]. This pleasant surprise in our literature survey demonstrates the efficacy of employing movement illusions to achieve vivid and distinctive tactile stimulation patterns using only a few tactors. It offers promising evidence for the haptic sense to be an effective information transmission channel.

C. Information Transmission With Force Displays

Tan [34] was the first to apply an information-theoretical approach to evaluating haptic object identification with a 3-degrees of freedom (DOF) force-feedback device capable of displaying force vectors in the x-, y-, and z-directions, and reported an IT of 2.0 bits for judging the sizes of hemispheres rendered virtually. Samur [102] compared three commercial force-feedback interfaces regarding their performance in rendering the size and shape of a virtual object. Performance with omega.3 (a 3-DOF force display by ForceDimension) was the highest at 1.74 bits, demonstrating the importance of device quality in transmitting force information. Using a 3-DOF force-feedback device augmented with a pneumatic tactile pulse display (see Fig. 14), Santos-Carreras *et al.* [103] showed that participants could identify the orientation of a virtual artery with an IT value of around 1.7 bits. Hatzfeld *et al.* [104] designed a passive force-feedback joystick using a magnetorheological elastomer actuator, and reported an IT of 0.83 bits for recognition of torque profiles. Cholewiak *et al.* [46] used a custom-designed 3-DOF force display (the "ministick") to study human haptic perception, and reported an IT of 1.54 bits for force–magnitude identification and 1.46 bits for stiffness identification. Overall, very few studies have explored the information capacity of force displays and the IT results

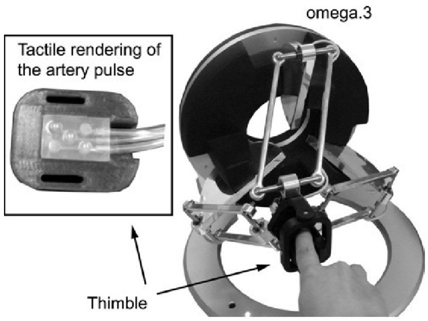


Fig. 14. *3-D force-feedback interface (omega.3, ForceDimension) augmented with a pneumatic tactile pulse display (from [103, Fig. 1]). The tactile display has five air chambers under a 0.3-mm silicone membrane in contact with the finger.*

with force displays are unremarkable. Additional research is needed to explore ways that information can be transmitted effectively through force-feedback devices.

D. Information Transmission Using Other Stimuli

A few studies evaluated the IT for other types of haptic stimuli. Lee and Lee [105] developed a prototype that stimulated the skin with compressed air delivered through four nozzles placed on the wrist or neck. Two successive air pulses indicated directional information (top, left, etc.). The IT was 1.35 bits on the wrist and 1.52 bits on the neck [105]. Wilson *et al.* [106] developed a thermal display using two Peltier modules on the palm. By controlling the heat intensity and temperature-change direction (increasing or decreasing), they showed an IT of 1.26 bits for thermal identification. Singhal and Jones [107] varied the direction, amplitude, and rate of change in temperature using a thermal display worn on the volar side of the wrist. They reported an IT of 2.13 bits for the identification of thermal patterns [107]. Like force displays, the information capacity of pneumatic and thermal devices awaits further investigation.

IV. CONCLUDING REMARKS AND GUIDELINES

The literature on the Tadoma tactual speech reception method used by individuals who are both deaf and blind provides an existence proof that the sense of touch is capable of receiving information as complex as speech at a near-normal rate [6], [108]–[111]. The information rate achievable by the Tadoma users has been shown to be 12 b/s [5], setting a high bar to be achieved by any haptic devices. The present survey article set out to review the literature on haptic interfaces that reports performance in terms of information transmission, a metric that transcends the differences in the physical parameters delivered by human–machine interfaces. We argue that this information-theoretical approach to interface design and human performance assessment provides a unified means for comparing human information-processing performance through not only the haptic but any other sensory channel. Due to the fact that most engineering professionals

Table 1 Guidelines for Maximizing Information Transmission

No.	Guidelines
#1	Lots of dimensions
#2	Few levels per dimension
#3	Use illusory movements

are not familiar with psychophysical methods, in general, and assessment of information transmission with humans, in particular, we have also provided a tutorial on absolute identification experiments that are typically used for estimating channel capacity. As far as we are aware, our tutorial contains the most comprehensive treatment of this topic, including the many practical issues to be considered in conducting a successful absolute identification experiment.

When we started this literature survey, we sought to find empirical evidence of strategies for high information transmission and high IT rate. We did not find many examples of IT rates, presumably due to the difficulties associated with training participants to become efficient at receiving a long sequence of stimuli. We suggest the use of an AXB paradigm for assessing the IT rate without long-term training and hope that new methods and results will emerge from this fertile and challenging research area.

As for strategies for achieving high IT, we sought evidence and indeed found ample data that supported strategies #1 and #2 in Table 1: Use lots of dimensions to create a rich information display, and use few levels per dimension to create distinct stimuli. Six decades ago, Geldard [112] wrote about "some neglected possibilities of communication" through the skin. He discussed the possibility of having "building blocks" along the continua of tactual perception so that appropriate stimulus arrays can be selected for coding given the nature of the messages to be communicated. The recommended dimensions for mechanical vibrations included locus, intensity, duration, and frequency. Additional possible dimensions were intensity as a function of time, waveform variations, and spatially discrete loci. The studies covered in this literature review provide further evidence that Geldard's recommendations have withstood the test of time.

In addition, we found strong evidence that haptic stimuli involving movement illusions can lead to higher IT than those that do not. Traditionally, tactors are turned on or off and the locations of the tactors and their ON/OFF states are used to convey information to a human user. Recently, more researchers are using perceptual illusions such as sensory saltation [26], [113] and apparent motion [68], [85] on multiple tactors to deliver stimuli that are perceived to be moving across the skin surface. Such stimuli can be used to encode additional properties such as movement direction and distance that are quite salient. For example, a recent study used only four tactors stimulating the index and ring fingers of two hands (see Fig. 9) [60]. It demonstrated a high IT of 7.02 bits with distinct spatiotemporal vibration patterns that contained illusory movement sequences among the four tactor

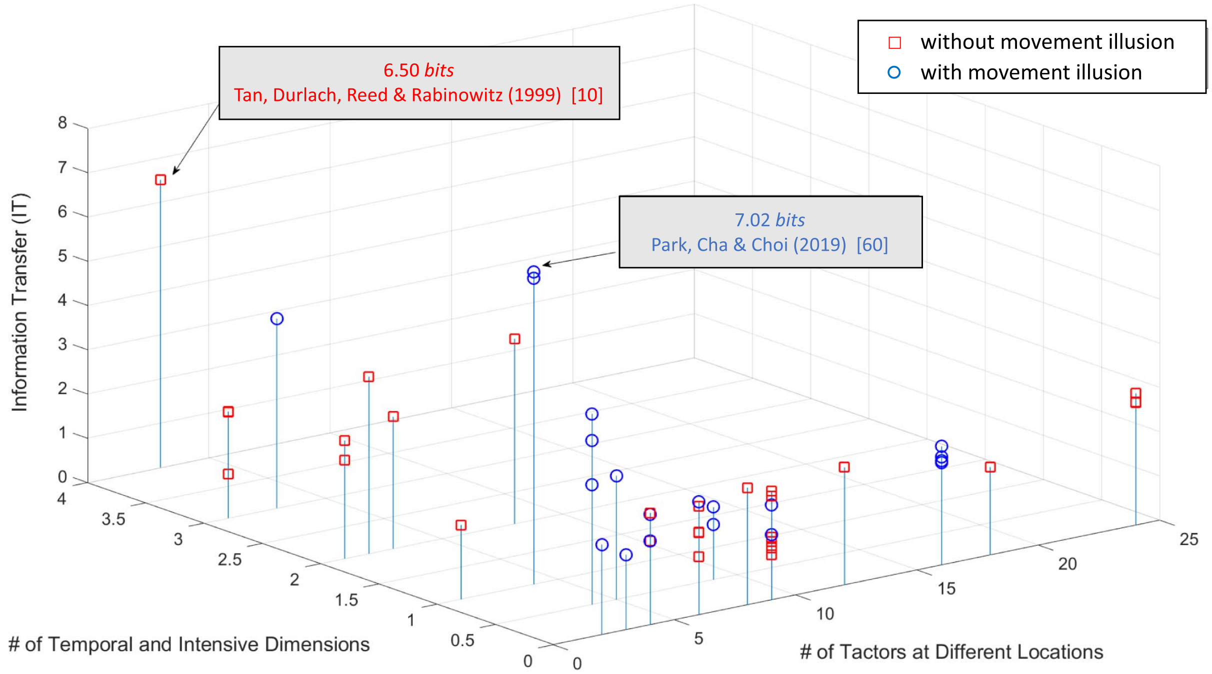


Fig. 15. ***IT values reported in previous studies with haptic stimuli. See Table 2 for the sources of the data points plotted here.***

locations, and with vibrations at two durations and two frequencies. Therefore, we add to Table 1 strategy #3: Use illusory movement patterns to create vivid and memorable stimuli that are easy to learn and remember.

From the literature reviewed in Section III, a majority of research on haptic communication relied on tactile stimuli owing to the simplicity of implementation, ease of use, extendibility to multiple channels and flexible form factor. Fig. 15 visualizes the ITs from the literature on tactile stimuli as a function of: 1) the number of temporal and intensive dimensions (e.g., signal amplitude, frequency, duration, amplitude modulation, rhythm, etc.); 2) the number of tactors at different locations; and 3) the use of movement illusions (blue circles) or not (red squares). The sources for the data points plotted in Fig. 15 are listed in Table 2, in the order of their appearance from left to right in the data plot. One can observe a general trend of increasing IT as the number of temporal and intensive dimensions increases. IT does not increase significantly as the number of tactors at different locations increases. This may be partly attributed to the poor numerosity judgment on the skin [114]–[116]. For example, Gallace *et al.* [114] placed seven tactors on the torso, forearms, and lower legs in nonsymmetric positions, and asked participants to report the perceived number of tactors on each trial. The overall numerosity judgment performance was quite poor: errors were recorded when only one tactor was activated, above 20% when two tactors were activated and above 50% when the number of tactors simultaneously activated was above 2.

In comparison, stimuli that use movement illusions (blue circles in Fig. 15) tend to result in higher ITs compared with red squares given similar numbers of temporal and intensive dimensions and of tactors at different locations. Two studies with exceptionally high information transfers are highlighted in Fig. 15. The highest IT with stimuli that do not use movement illusions is 6.50 bits, reported by Tan *et al.* [10] using the Tactutor that delivered motional, fluttering, and vibrotactile sensations to multiple digits. The highest IT with stimuli that use movement illusions is 7.02 bits, reported by Park *et al.* [60] that stimulated the thumbs and index fingers of both hands using spatiotemporal stimulation patterns. The data presented in Fig. 15 provide ample empirical evidence that supports the guidelines presented in Table 1.

Our guidelines are generalizable to other types of haptic stimuli and other sensory modalities. The research on haptic communication using stimuli that involve skin stretch, force, air pressure, and temperature, etc. does not provide sufficient data for us to draw useful general guidelines at the present time. We encourage and hope for future research endeavors that will fill this gap in knowledge.

We end this tutorial and survey article with a recent success of devising a skin-based speech communication system that encodes the 39 English phonemes into distinct and meaningful vibrotactile stimulation patterns delivered through a TActile Phonemic Sleeve (TAPS) system, a 24-tactor array placed on the forearm [117]–[121]. The survey results presented in this article provided the guidelines for the most efficient and fastest route to designing vibrotactile phonemic codes and training people to receive English words on the skin. In developing TAPS, we used multiple dimensions (frequency, waveform, duration, location, amplitude modulation), few

Table 2 Sources for Data Points in Fig. 15, in the Order of Their Appearance From Left to Right

Reference	Use of Movement Illusions (○) or Not (□)	# of Temporal and Intensive Dimensions	# of Tactors at Different Locations	*IS* (*bits*)	*IT* (*bits*)	Notes
Tan et al. (1999) [10]	□	4	3	6.91	6.50	
Summers et al. (1997) [73]	□	3	1	1.92	1.00	
Chen et al. (2011) [51]	□	3	1	5.91	2.40	
Azadi & Jones (2014) [78]	□	3	1	3.17	2.41	
Lee & Starner (2010) [96]	○	3	3	4.58	4.28	
Sherrick (1985) [72]	□	2	1	3.32	2.23	Min
Sherrick (1985) [72]	□	2	1	3.32	2.67	Max
Rabinowitz et al. (1987) [58]	□	2	2	6.97	4.00	Contact area as an additional dimension
Brown et al. (2006) [79]	□	2	3	4.75	2.98	Forearm
Ryu et al. (2010) [81]	□	1	1	2.32	1.68	
Barralon et al. (2007) [70]	□	2	8	6.17	4.18	
Park et al. (2019) [60]	○	1	4	7.39	6.88	Fingers
Park et al. (2019) [60]	○	1	4	7.39	7.02	Phone
Hsieh et al. (2016) [92]	○	0.5	4	3.32	2.71	Different durations for some stimuli
Seo & Choi (2015) [100]	○	0.5	4	5.00	3.70	Different durations for some stimuli
Liao et al. (2016) [97]	○	0.5	4	4.70	4.31	Different durations for some stimuli
Culbertson et al. (2017) [93]	○	0	2	2.58	2.04	Asymmetric vibrations
Yatani & Truong (2009) [99]	○	0.5	5	3.46	2.80	Different durations for some stimuli
Culbertson et al. (2017) [93]	○	0	3	2.58	1.70	Asymmetric vibrations
Park & Choi (2018) [82]	□	0	4	3.17	1.89	2D Phantom sensations
Matscheko et al. (2010) [94]	○	0	4	3.00	1.90	
Matscheko et al. (2010) [94]	○	0	4	3.00	2.49	
Park & Choi (2018) [82]	□	0	4	3.17	2.53	2D Phantom sensations
Wong et al. (2010) [77]	□	0	6	2.32	1.32	Min
Wong et al. (2010) [77]	□	0	6	2.32	1.84	Max
Israr et al. (2016) [86]	□	0	6	2.58	1.87	
Cholewiak et al. (2004) [80]	□	0	6	2.58	2.46	
Israr et al. (2016) [86]	○	0	6	3.00	2.55	
Lee et al. (2015) [95]	○	0.5	9	2.00	1.24	Min
Lee et al. (2015) [95]	○	0.5	9	2.00	1.64	Max
Cholewiak et al. (2004) [80]	□	0	8	3.00	2.65	
Sofia & Jones (2013) [75]	□	0	9	3.17	1.02	
Sofia & Jones (2013) [75]	□	0	9	3.17	1.17	
Sofia & Jones (2013) [75]	□	0	9	3.17	1.32	
Sofia & Jones (2013) [75]	□	0	9	3.17	1.42	
Jones et al. (2009) [98]	○	0	9	3.00	1.48	Min
Jones et al. (2009) [98]	○	0	9	3.00	2.15	Max
Sofia & Jones (2013) [75]	□	0	9	3.17	2.34	
Sofia & Jones (2013) [75]	□	0	9	3.17	2.46	
Cholewiak et al. (2004) [80]	□	0	12	3.58	2.66	
Jones et al. (2009) [98]	○	0	16	2.81	2.31	
Jones et al. (2009) [98]	○	0	16	2.81	2.36	
Jones et al. (2009) [98]	○	0	16	2.81	2.44	
Jones et al. (2009) [98]	○	0	16	2.81	2.68	
Chen et al. (2008) [74]	□	0	18	4.17	1.99	
Cholewiak & McGrath (2006) [24]	□	0	24	4.58	2.77	
Cholewiak & McGrath (2006) [24]	□	0	24	4.58	2.78	
Cholewiak & McGrath (2006) [24]	□	0	24	4.58	2.98	

levels per dimension (mostly 2), and movement illusions for encoding (the longer) vowels. Our results by Reed *et al.* [119] demonstrated that people can indeed learn the 39 haptic symbols for phonemes with a mean recognition rate of 86% correct within one to four hours of training. Impressively, owing to the strategy of encoding consonants at specific locations and encoding vowels with spatiotemporal illusory movement patterns, our participants rarely confused a consonant with a vowel or vice versa [119]. Our recent results on word recognition performance by Tan *et al.* [121] showed that among a total of 51 participants, the best participants were able to learn 500 English words with an average rate of one English word per minute. In addition to revising the haptic symbols for increased transmission rates [120], two trained participants have started sending short text messages to each other using a text-to-speech (TTS) front-end to TAPS. The findings from this ongoing research project will shed light on the continuous use of TAPS in terms of learning time, possible after-effects, and the ultimate information transmission rate that can be achieved.

We hope that the methodology and guidelines presented in this article will stimulate further research in the use of an information-theoretic framework to assess human performance, and lead to new insights on increasing information transmission with tactile, haptic, or other multisensory and multimodal human–machine interfaces. ■

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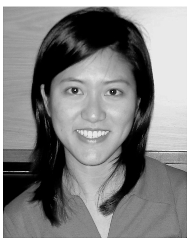

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